International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

Physics-Informed Machine Learning for Specific Cutting Energy in Abrasive Waterjet Cutting: A Simulation-Based Feasibility and Sustainable Process-Planning Study

Ketan D. Panchal[1]
[1]Dr. S. & S.S. Ghandhy Government Engineering College, Surat, Gujarat, India

Abstract
Background: Abrasive waterjet (AWJ) cutting combines erosion-based material removal with substantial hydraulic and electrical energy demands. Physics-informed learning could potentially improve data efficiency, but this proposition needs careful evaluation before experimental claims are made. Objective: This simulation-based methodological study examines a physics-guided modelling framework for abrasive specific cutting energy, material removal rate (MRR) and kerf taper in 6-mm austenitic stainless-steel cutting. Methods: A proposed 44-setting design comprises 30 face-centred central composite design (CCD) settings for fitting and 14 interior Latin-hypercube settings for testing. Analytical abrasive power is coupled with neural-network prediction through feature, residual and energy-balance formulations and compared with response-surface regression (RSM), a conventional artificial neural network, Gaussian process regression and gradient boosting. Results: In the supplied simulation, residual physics-informed learning (PIML-R) achieved a test MAPE of 2.84% (R^2 = 0.979) for abrasive specific energy, compared with 2.99% (R^2 = 0.978) for quadratic RSM and 3.26% (R^2 = 0.970) for the conventional ANN. Confidence intervals overlapped. A simulated process-planning example indicated approximately 12% lower modelled electricity demand per 100-mm cut relative to a centre-point setting; this estimate depends on assumed pump efficiency and grid-emission intensity. Conclusion: The computational example illustrates a feasible workflow, not experimentally demonstrated superiority or energy savings. Measured AWJ cutting data and independently verified power consumption are required before engineering deployment.

Keywords: abrasive waterjet; physics-informed machine learning; specific cutting energy; simulation; response surface methodology; energy efficiency; sustainable manufacturing

*Corresponding author: Ketan D. Panchal, Dr. S. & S.S. Ghandhy Government Engineering College, Surat, Gujarat, India

1. Introduction

Abrasive waterjet cutting is used for metals, ceramics and composites because the material removal mechanism produces negligible conventional thermal damage. Nevertheless, high-pressure pumping and abrasive use create an energy–productivity–quality trade-off. Evaluation must distinguish the kinetic energy imparted to abrasive particles from the hydraulic energy delivered by the jet and the electrical energy drawn by the cutting system (Hashish, 1989; Janković et al., 2018). Prior analytical models provide interpretable relationships between jet pressure, mixing and particle energy, whereas data-driven regressors can accommodate nonlinear process behaviour (Narayanan et al., 2013; Panchal and Shaikh, 2021). A physics-informed residual model offers a plausible

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

intermediate approach: the physical formula supplies a baseline and machine learning captures deviations. Its benefit cannot, however, be inferred from fit on simulated outcomes alone.

The present manuscript therefore reports a simulation-based feasibility analysis and a fully specified experimental validation design. The numerical summaries and comparisons are taken from the supplied simulation draft; the underlying per-run response data and executable code were not available for independent recalculation. No physical cutting experiment or confirmation test is claimed here.

2. Physics-based formulation

For water density ρw, pressure P, orifice diameter do and discharge coefficient φ, the ideal Bernoulli-based jet speed with an empirical discharge adjustment is $v_j = \varphi(2P/\rho_w)^{1/2}$. The approximate water mass flow is $\dot{m}_w = \rho_w(\pi d_o^2/4)v_j$. With abrasive mass flow $\dot{m}_A$ and a mixing-loss coefficient β, an illustrative momentum-based abrasive exit velocity is $v_a = \beta \dot{m}_w v_j/(\dot{m}_w + \dot{m}_A)$. The abrasive-stream kinetic power is $\dot{E}_{abr} = 0.5 \dot{m}_A v_a^2$. These are modelling assumptions; β and φ require empirical calibration.

Material removal rate is $MRR = \Delta m/(\rho_s t_{cut})$ (mm^3/s when consistent units are applied), where Δm is coupon mass removed, ρs is steel density and tcut is cutting time. Specific abrasive cutting energy is $E_{sp,abr} = \dot{E}_{abr}/MRR$. Analogously, $E_{sp,hyd} = (P\,Q)/MRR$ and $E_{sp,elec} = P_{elec}/MRR$; the three metrics must not be described interchangeably. Pump electrical power was not measured for the present simulation.

The draft proposed φ in the range 0.88–0.95 and β in 0.65–0.85. In the supplied numerical example, φ was held at 0.915 because separate identification of φ and β from specific-energy observations was not established; only β was fitted. This choice supersedes the inconsistent statement in the original methods that both quantities were trainable.

3. Computational study design and proposed experimental validation

3.1 Materials and factor space

The proposed physical validation uses 6-mm-thick austenitic stainless-steel coupons, a DWJ-1313-FB AWJ system, a 0.25-mm orifice, a 1.02-mm focusing tube, 80-mesh garnet and a nominally normal jet incidence. These details specify a prospective experimental setup, not a confirmation that physical trials were performed for this study.

Factor	Symbol	Low (−1)	Centre (0)	High (+1)
Water pressure (MPa)	P	220	250	280
Abrasive mass flow rate (g/min)	ṁ_A	250	350	450
Traverse speed (mm/min)	S	40	60	80
Standoff distance (mm)	h	2	3	4

3.2 Sampling and evaluation protocol

A four-factor face-centred CCD consists of 16 factorial combinations, eight axial points and six centre replicates (30 modelling settings). Fourteen separate Latin-hypercube interior settings are

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

reserved as a prospective independent test set. The complete 44-setting schedule is reproduced in Appendix A. The design is a planned sampling scheme and should not be labelled an observed dataset until responses have been measured. Randomized execution, nozzle-condition records and independent measurement logs are recommended to control drift.

The supplied draft describes repeated 5-fold cross-validation (10 repeats) for tuning within the 30-point CCD partition and a single evaluation on the 14 Latin-hypercube settings. Repeated cross-validation folds share observations and should not be treated as statistically independent replicates. Because the input-response table and scripts were not provided, hyperparameter searches, fold assignments and reported tests could not be audited independently.

3.3 Physical validation measurements

For eventual experimental evaluation, record coupon masses, cut time, top and bottom kerf width at three positions, pressure, abrasive throughput, and the electrical power time series. Kerf taper can be estimated as $\arctan[(W_{top} - W_{bottom})/(2t)]$, where t is plate thickness. Replicate cuts at representative conditions and report sensor calibration, uncertainty, steel grade, cutting length, machine operating state and any excluded failed cuts. Energy boundaries should include cutting versus idle power explicitly.

4. Physics-informed prediction and comparators

Three candidate implementations are considered: (i) PIML-F, where analytical abrasive power is an additional input; (ii) PIML-R, where $\ln(E_{sp,abr})$ equals a physics-based baseline plus a neural residual; and (iii) PIML-L, where the training objective penalizes violation of $E_{sp,abr} \times MRR = \dot{E}_{abr}$ and, where justified, physically implausible pressure trends. The comparators are quadratic RSM, a conventional ANN, Gaussian process regression and gradient boosting. The supplied results contain no separate quantitative evaluation of PIML-L; no performance claim is made for it.

Predictions are compared using MAE, RMSE, MAPE and R^2 on the same response and units. Ensemble prediction intervals are judged by held-out empirical coverage. A 95% interval containing 13 of 14 cases corresponds to approximately 93% coverage; the granularity of a 14-case test limits interpretation. Interpretability analysis using SHAP and partial-dependence plots remains prospective because those plots were not included in the source.

5. Simulation results

All numerical results in this section are SIMULATED values supplied in the original draft. They are not experimental measurements and were not independently reproduced from raw responses or code.

5.1 Response and RSM summaries

Response	Min	Max	Mean at centre point (n = 6)	Centre-point CV (%)
MRR (mm^3/s)	3.60	9.22	6.22	3.0
$E_{sp,abr}$ (J/mm^3)	37.78	153.57	77.53	3.1
$E_{sp,hyd}$ (J/mm^3)	753.96	2487.44	1284.65	3.0
$E_{sp,elec}$ (J/mm^3)	864.11	2877.72	1510.22	2.8
Kerf taper (°)	0.62	2.48	1.53	5.1

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

Table 1. Reported simulated response summary (not physical measurements).

Response	R^2	Adjusted R^2	Model p-value	Lack-of-fit p-value
ln E_sp, abr	0.997	0.994	5.6e-16	0.85
ln MRR	0.996	0.992	3.1e-15	0.83
Taper (°)	0.985	0.971	4.1e-11	0.72

Table 2. Reported simulated quadratic-RSM fit statistics. Nominal p-values are descriptive of the chosen simulation, not empirical confirmation of real cutting behaviour.

5.2 Simulated model comparison

Model	CV MAPE (%)	Test MAE (J/mm³)	Test RMSE (J/mm³)	Test MAPE (%) [95% CI]	Test R^2	95% interval coverage (%)
RSM (quadratic)	3.46	2.55	3.06	2.99 [2.1, 4.0]	0.978	n/a
ANN (2021-type)	4.21	2.76	3.59	3.26 [2.0, 4.7]	0.970	n/a
Gaussian process	3.14	2.88	3.48	3.37 [2.4, 4.4]	0.972	86
Gradient boosting	4.89	7.29	8.39	9.50 [7.0, 12.2]	0.835	n/a
PIML-F	4.19	2.74	3.42	3.27 [2.1, 4.5]	0.973	n/a
PIML-R	3.52	2.43	2.98	2.84 [2.0, 3.7]	0.979	93

Table 3. Reported simulated cross-validation and independent interior test-set performance; predictions concern abrasive specific energy. CI = reported confidence interval; n/a = not available.

Within this computational illustration, PIML-R had the smallest reported test MAPE (2.84%) and test RMSE (2.98 J/mm³). The RSM model performed similarly (MAPE 2.99%; RMSE 3.06 J/mm³), and the reported MAPE confidence intervals overlap. These summaries do not establish statistically robust superiority. The source also reported a Wilcoxon p-value of 0.028 for PIML-R versus ANN over repeated CV folds; because folds share observations and no fold-level data were provided, this value is not used as confirmatory inference.

5.3 Data-efficiency sensitivity

Training runs	RSM	ANN	Gaussian process	PIML-F	PIML-R
10	n/a (<16 runs)	4.3	4.0	4.1	7.0
15	n/a (<16 runs)	3.8	3.3	3.6	4.2
20	3.1	3.6	3.3	3.5	2.9
25	3.0	3.1	3.4	3.3	2.8
30	3.0	3.3	3.4	3.3	2.8

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

Table 4. Reported simulation-based learning-curve MAPE (%).

The residual physics model was weaker than the conventional ANN at 10 and 15 training settings, but comparatively favourable at 20–30 settings. Therefore, the supplied results support only a conditional, simulation-specific data-efficiency hypothesis. A full quadratic model with 15 terms requires sufficient independent design points and may become unstable with minimal sampling.

5.4 Parameter identifiability and constraints

The source reports a simulated estimate $\beta = 0.745$ (bootstrap 95% interval 0.743–0.746), close to the $\beta = 0.74$ used to generate the simulation. This agreement is expected when the generating model and the fitted physical baseline are closely aligned and is not an independent validation of the loss factor. With φ held at 0.915, simultaneous identification of φ and β was not assessed. Extrapolation and boundary-condition plausibility were not tested, since the Latin-hypercube test points were interior.

6. Exploratory process planning and sustainability

The source describes an exploratory random search over candidate settings and a multi-criterion compromise selection. Although NSGA-II is proposed in the methods, no reproducible population size, generation count or operator settings were provided; the available evidence therefore does not support claiming a completed, reproducible NSGA-II study. The draft reports 449 non-dominated solutions among the first 4,000 dominance-filter passes after sampling 40,000 candidates; the relationship between these counts requires code-level reconciliation.

The reported compromise setting is P = 273.5 MPa, abrasive flow = 449 g/min, traverse speed = 78 mm/min and standoff = 2.0 mm. The reported confirmation outcomes—MRR 7.99 mm^3/s, electrical specific energy 1345 J/mm^3 and taper 1.18°—are SIMULATED confirmation cuts, not laboratory observations. The choice lies near the design-space boundary and needs actual verification.

Item (per 100 mm of cut, 6 mm thick)	**How to calculate**	**Baseline (250 MPa, 350 g/min, 60 mm/min, 3 mm)**	**Optimum (273.5, 449, 78.0, 2.0)**
Pump electrical energy (kWh)	Pump power × cutting time	0.259	0.228
Garnet used (kg)	Flow rate × cutting time	0.583	0.575
Cutting time (min)	Length ÷ traverse speed	1.67	1.28
CO_2-equivalent from electricity (kg)	Energy × 0.71 kg/kWh (assumed factor)	0.184	0.162

Table 5. Source-reported SIMULATED inventory per 100 mm cut in a 6-mm plate. Electrical energy assumes pump efficiency of 0.85; electricity-related CO_2-equivalent assumes 0.71 kg/kWh.

On the specified functional unit, the source estimates a decrease in modelled electricity from 0.259 to 0.228 kWh (approximately 12%) and cutting time from 1.67 to 1.28 min (approximately 23%). These are hypothetical operating-point comparisons, not measured environmental benefits. Garnet extraction, water treatment, waste management and machine standby energy are excluded. A dated

geographically appropriate electricity emission factor and measured pump load are needed before making site-specific carbon claims.

7. Discussion and limitations

The key methodological contribution is the explicit separation of analytical abrasive power, machine-level electricity use and the data-driven residual. The simulation illustrates that physics-guided correction can perform comparably to conventional RSM in a small designed sample, but the close observed scores and overlapping intervals preclude categorical ranking. Stronger reported simulation performance may partly reflect correspondence between the synthetic data generator and the physical assumptions embedded in the learner.

This study has important limitations: (1) no observed 44-run response dataset or measured electrical traces were supplied; (2) all reported fit statistics and optimisation outcomes are simulated; (3) the synthetic data and analysis code were not available for independent numerical verification; (4) only a single nominal alloy thickness and machine configuration were considered; (5) test points are interior rather than genuine boundary or external-validation cases; (6) no completed SHAP figures or PIML-L comparison were supplied; and (7) carbon and pump-efficiency assumptions are illustrative. Consequently, the paper should be evaluated as a simulation-based framework demonstration, not as experimental proof of performance or sustainability.

8. Conclusions

A combined analytical and residual machine-learning framework for abrasive specific cutting energy was outlined and illustrated using the simulation summaries supplied in the source manuscript. In that simulation, PIML-R achieved test MAPE 2.84% and R^2 0.979, only marginally different from quadratic RSM (MAPE 2.99%, R^2 0.978). The explored operating-point comparison suggested approximately 12% less assumed pump electricity per 100-mm cut, but no physical energy saving was measured. Before the methodology can support manufacturing decisions, the authors should execute the proposed 44-run design, release the response-level data and analysis code, measure machine electricity and confirm optimum settings on the cutting system. The present conclusions are restricted to computational feasibility.

Declarations

Acknowledgments

The author gratefully acknowledges the institutional support and academic environment provided by Dr. S. & S.S. Ghandhy Government Engineering College, Surat, Gujarat, India. The author also appreciates the contributions of researchers whose published work provided the theoretical foundation for this study.

Conflict of Interest

The author declares that there are no known financial or non-financial conflicts of interest that could have influenced the research, analysis, interpretation, or preparation of this manuscript.

Funding:

None

References

1. Chithirai Pon Selvan, M., et al. 2020. A mathematical modelling of abrasive waterjet machining on Ti–6Al–4V using artificial neural network. Materials Today: Proceedings. doi:10.1016/j.matpr.2019.12.215

2. Finnie, I. 1960. Erosion of surfaces by solid particles. Wear 3(2): 87–103.
3. Hashish, M. 1989. A model for abrasive waterjet (AWJ) machining. Journal of Engineering
4. Materials and Technology 111(2): 154–162.
5. Himmelreich, U. 1992. Fluiddynamische Modelluntersuchungen an Wasserabrasivstrahlen. VDI-Fortschritt-Berichte, Reihe 7, Nr. 219.
6. Janković, P. L., Madić, M. J., Petković, D. L., and Radovanović, M. R. 2018. Analysis and modeling of the effects of process parameters on specific cutting energy in abrasive water jet cutting. Thermal Science 22: S1459–S1470.
7. Nambiath, P., Galecki, G., and Summers, D. A. 2007. Energy based modelling of abrasive slurry jet. WJTA American Waterjet Conference, Houston.
8. Narayanan, C., Balz, R., Weiss, D. A., and Heiniger, K. C. 2013. Modelling of abrasive particle energy in water jet machining. Journal of Materials Processing Technology 213(12): 2201–2210.
9. Panchal, K. D., and Shaikh, A. H. 2021. Performance analysis and process parameters optimisation on specific cutting energy in the abrasive waterjet cutting. International Journal of Ambient Energy. doi:10.1080/01430750.2021.1873851
10. Panchal, K. D., and Shaikh, A. H. 2022. Depth of penetration model in AWJ cutting process considering the effect of frictional drag of kerf wall on the water-jet velocity. Smart and Sustainable Manufacturing Systems 6(1): 1–10. doi:10.1520/SSMS20210018
11. Shukla, M., and Tambe, P. B. 2010. Predictive modelling of surface roughness and kerf widths in abrasive water jet cutting of Kevlar composites using neural network. International Journal of Machining and Machinability of Materials 8(1–2): 226–246.
12. Srinath Reddy, N., Tirumala, D., Gajjela, R., and Das, R. 2018. ANN and RSM approach for modelling and multi objective optimization of abrasive water jet machining process. Decision Science Letters 7(4): 535–548.
13. Uhlmann, E., and Männel, C. 2019. Modelling of the kerf formation through primary and secondary jet energy for the abrasive waterjet. WJTA American Waterjet Conference.
14. Wang, J. 2007. Predictive depth of jet penetration model for abrasive water jet cutting of alumina ceramics. International Journal of Mechanical Sciences 49(3): 306–316.
15. Zhang, P., and Nambiath, S. 2005. Accurate hole drilling using an abrasive water jet in titanium. WJTA American Waterjet Conference, Houston

Appendix A. Proposed 44-setting design (not executed study runs)

Run	Set	P (MPa)	ṁ_A (g/min)	S (mm/min)	h (mm)
1	CCD factorial	280	450	40	4
2	LHS test	277	274	77	2.2
3	LHS test	251	297	60	2.1
4	LHS test	263	259	73	2.6
5	CCD axial	250	350	80	3
6	CCD factorial	220	450	40	4
7	LHS test	231	287	56	3.5
8	CCD factorial	220	250	80	4
9	CCD factorial	220	450	80	4

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

Run	Set	P (MPa)	ṁ_A (g/min)	S (mm/min)	h (mm)
10	CCD factorial	280	250	80	4
11	LHS test	258	347	67	2.7
12	CCD factorial	280	250	40	4
13	CCD axial	220	350	60	3
14	CCD centre	250	350	60	3
15	CCD factorial	220	250	40	2
16	LHS test	226	434	51	3.8
17	CCD factorial	280	250	40	2
18	CCD factorial	280	450	40	2
19	LHS test	235	377	64	2.4
20	CCD factorial	280	450	80	4
21	CCD centre	250	350	60	3
22	CCD axial	250	250	60	3
23	CCD axial	250	350	40	3
24	CCD factorial	280	250	80	2
25	CCD factorial	220	450	40	2
26	LHS test	239	311	77	2.4
27	LHS test	243	440	46	3.1
28	CCD factorial	220	450	80	2
29	LHS test	274	384	43	3.6
30	CCD axial	250	350	60	4
31	LHS test	271	328	41	3.9
32	CCD axial	250	350	60	2
33	CCD factorial	220	250	40	4
34	CCD centre	250	350	60	3
35	CCD centre	250	350	60	3
36	LHS test	249	410	61	3.3
37	CCD factorial	220	250	80	2
38	CCD axial	280	350	60	3
39	CCD axial	250	450	60	3
40	CCD centre	250	350	60	3
41	CCD factorial	280	450	80	2
42	CCD centre	250	350	60	3
43	LHS test	223	364	71	3.0
44	LHS test	265	403	52	3.3